

AI-Driven Enterprise Architecture Transformation Across Traditional Industrial Cities in Saudi Arabia

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Abstract

Saudi Arabia's traditional industrial cities, comprising Riyadh Industrial City, Jeddah Industrial City, Dammam Industrial Cities, and Jubail Industrial City, are recognized as the cornerstone of national manufacturing, logistics, petrochemicals, and industrial services.

With the acceleration of digital transformation by the Vision 2030 agenda (Saudi Vision 2030. n.d), these cities are under escalating pressure to modernize legacy systems and adopt Industry 4.0 technologies (Kagermann et al., 2013; Lu, 2017) is being experienced by these cities.

Enterprise Architecture (EA) across these environments remains fragmented, outdated, and dominated by manual documents that hinder architectural visibility and impede modernization (Lankhorst, 2017).

In this Action Research study, investigation was conducted into how artificial intelligence (AI) can be deployed to improve EA practices, diminish technical debt (Ozkaya, 2021), and improve decision support in many industrial cities.

By using iterative Plan → Act → Observe → Reflect cycles (Reason & Bradbury, 2018), this study implemented AI for architectural discovery, dependency analysis, predictive technical debt modeling, and dynamic visualization dashboards across 11 industrial cities. The interventions achieved a 70-plus percent decrease in architectural mapping time, raised the accuracy of documentation from 60 to 92 percent, and a marked increase in cross functional collaboration (Accenture, 2023; McKinsey & Company, 2023).

Organizations showed increased preparedness for modernization initiatives, better alignment with demands of Industry 4.0, and better governance maturity.

AI-driven EA has been identified as a strategic enabler to support industrial modernization: more than just a technical upgrade: an analysis of this approach concluded that the EA.

A replicable template for industrial clusters was offered through this approach aiming to strengthen architectural governance, spur digital transformation, and cultivate long-term operational resilience (Ross et al., 2006; Kruchten et al., 2012).

Keywords:

Enterprise Architecture; Artificial Intelligence; Digital Transformation; Operating Models; Industry 4.0.

1. Introduction

Traditional industrial cities in Saudi Arabia (Riyadh Industrial City, Jeddah Industrial City, Dammam Industrial City, and Jubail Industrial City) support the Kingdom's manufacturing and logistics sectors, as well as its petrochemical and industrial services. These cities have many interconnected systems: manufacturing lines, supply chain operations, utilities, administrative processes and industrial services. This shift towards digital transformation has now become a national focus of the Kingdom as Vision 2030 is implemented, necessitating industrial cities to update legacy systems, shore up operational resilience, and transition to Industry 4.0 technologies like Internet of Things (IoT), cyber physical systems, predictive maintenance, and AI enabled automation (Kagermann et al., 2013; Lu, 2017).

Through Vision 2030, industrial diversification, digital capability development and smart infrastructure are explicit, thus the modernization of industrial city architecture becomes a strategic rather than isolated technical priority (Ministry of Industry and Mineral Resources, 2023).

To meet this national momentum, however, Enterprise Architecture (EA) in these industrial infrastructures are fragmented, aged and based largely on manual documentation. Most businesses continue to rely on static diagrams, siloed inventories, and partial maps, which does not illustrate how things operate in real time. With these limitations, structural barriers are encountered that impede modernization, expose businesses to operating risk, and impede the uptake of new, advanced technologies.

Technical debt compounds itself over time in legacy systems; undocumented integration points result in operational blind spots; modernization decisions are reactive, rather than strategic (Kruchten et al., 2012).

In practice, difficulty is often experienced by EA teams in learning the process required to cope with constant system changes, ad hoc integrations, and project-driven fixes, leading to architectures that are more "assumed" than really understood.

The difficulty is not one only of Saudi Arabia. There are global challenges within industrial organizations to maintain quality architectural documentation as these

organizations have the difficulty to keep a precise architectural documentation owing to their complex system, technological change in an ever-faster pace and the inherent limitation of traditional EA frameworks such as TOGAF and Zachman (Lankhorst, 2017; Ross et al., 2006).

These frameworks are developed to deliver systematic approaches and governance models, but their nature is based more on methods and have substantial reliance on manual nature which is not sustainable in fast moving industrial practices.

Therefore, EA teams often function with legacy data, unable to support modernization initiatives, manage technical debt, or provide leadership with strategic advice (Kotusev, 2021).

EA is viewed more as a compliance or documentation-based activity rather than a dynamic decision support capability, further decreasing its contribution to transformation initiatives (Kotusev, 2021). According to the International Telecommunication Union (2021), these challenges are exacerbated in Saudi Arabia due to the scale of industrial operations, regulatory requirements, and interoperability requirement across government agencies, private sector organizations, and industrial clusters.

Industrial cities are to be in close touch with the modernization of diverse stakeholders like manufacturers, logistics providers, utilities, financial services and regulatory entities. These stakeholders have difficulty aligning modernization priorities, assessing risks, or properly aligning investments without proper architectural insights. Mismatched activities can result in redundant systems, inconsistent data, or fragmented digital experiences, compromising the broader visions and aspirations of Vision 2030 and Industry 4.0. Artificial Intelligence (AI) provides a disruptive possibility to modern EA practices and addresses these structural obstacles.

Tools powered by AI for this purpose can automate architectural and process discovery, uncover hidden or undocumented system dependencies, as well as enable machine learning models to anticipate risk of failed systems (Accenture, 2023).

With those capabilities, organizations can quickly create realistic architectural baselines, surface hidden threats and inform data-led modernization plans.

AI provides the ability to map architectures in near real time and reveal shadow systems in thousands of critical operations in the world's industrial city contexts, exposing vulnerabilities that might otherwise go unnoticed (McKinsey & Company, 2023).

AI powered visualization platforms can represent intricate dependency networks to the customer in easy-to-follow formats, allowing them to see the impact of designs in a much clearer way for both technical and business players. AI also supports decision making by delivering dynamic dashboards, predictive analytics, and automated impact analysis. Such tools enable business leaders to analyze the impact of modernization decisions, understand the level of technical debt, and focus investments accordingly that are driven by real time insights rather than stale documentation (World Economic Forum, 2023). For instance, AI-based models could help estimate the risk and cost of maintaining certain outdated, legacy elements and to simulate the modernization approach and suggest some possible migration routes to an optimal path.

This takes EA out of a stagnant documentation-based process, and makes it instead a consistent, intelligence-based decision support task. But it takes more than technology to get organizations to adopt AI enabled EA.

It requires organizational transformation, capability development, and governance restructuring. Industry institutions need to build AI literacy, enhance EA governance and support cross functional cooperation if they hope to fully unlock the potential of AI (Westerman et al., 2014; Schein, 2010).

EA teams need an entirely new set of skills. Adaption of data analysis, interpretation of models and stakeholder communication is required in this new world. Incorporation of architectural insights into strategic planning is accepted by business leaders, while more transparent, collaborative way of working is sought by IT teams.

However, AI tools without these cultural changes and structural changes (CULTAI Independent Expert Group et al., 2025) will often find themselves employed only in the virtual (or a far cry) world where only a few have tried to find anything of practical use. Considering the above challenges and opportunities, the current study proposes to analyze how AI powered EA can speed up the transition from fragmented, legacy, manually-documented industrial systems to fully digital, AI-enabled, Industry 4.0-ready

infrastructures. This modernization includes upgrading technology, processes, governance, and operational models in the Saudi Arabian traditional industrial cities.

The methodology applied in this research is Action Research and is especially appropriate for complex organizational contexts in the process of change.

Action Research combines real world intervention, shared learning, and cycle iterations for the process and iteration, facilitating the development of solutions by academics and industry practitioners to iterate on them through feedback loops (Reason & Bradbury, 2015; Kemmis et al., 2014; Herr & Anderson, 2015).

iterative cycles (Plan → Act → Observe → Reflect) are used in several industrial cities so that structural issues can be identified, engineer AI interventions, observe their effects, and adapt approaches in response to feedback from stakeholders. By focusing on the actual organizational context, the methods make the findings grounded and represent the practices of practitioners working within the various industrial settings.

Combining academic rigor with practical consulting style engagement, the generation of findings is also intended to remain theoretically robust and directly applicable to industrial city authorities, EA teams, and organizational leaders alike.

Hence, this introduction sets the framework for this study by emphasizing the structural challenges that industrial cities are currently faced with and under-utilizing traditional EA practices to help fill such gaps, in which case AI has great potential.

Framing the research within the context of the broader National Transformation agenda and the worldwide trends of Industry 4.0 while offering a context for the application of Action Research as an appropriate methodology to impact change in the context of complex, multi-stakeholder interaction.

This builds on the foundation of methodology, intervention, findings and implications for practice in the next pages.

2. Methodology/approach

Action Research methodology has been employed in this study, which demonstrates that the methodology is in keeping with the need of the EIU Journal of Action Research and appropriate to the specific context of organizations transitioning to a digital environment.

Action Research encourages hands-on problem solving, experimentation and collaboration with relevant stakeholders in real-world operational contexts (Reason & Bradbury, 2018; Kemmis et al., 2014).

EA modernization is especially relevant in this environment, where EA-related issues are often interwoven with workplace processes, legacy systems, and cross-functional team interactions.

The research was conducted across 11 traditional industrial cities in Saudi Arabia's. These industrial cities cover industries ranging from manufacturing and logistics to utilities, industrial services and administrative operations. Including Enterprise Architects, IT Directors, Business Capability Owners, Operations Managers and Digital Transformation Leads, ensuring both technical and business perspectives were included.

These 11 industrial cities were chosen through purposive sampling method, aligning with Action Research principles, where sampling adequacy is primarily defined by relevance, as opposed to statistical representativeness through stakeholder participation.

The industrial cities were selected for their presence in a conventional set of industrial cities, complexity of legacy architectures, and engagement with modernization strategy in accordance with Vision 2030. Their diverse operating backgrounds created information-rich contexts vital for cyclical assessment, action, and reflection.

Consequently, industrial cities were classified based on access, relevance, and requiring continued stakeholder engagement across multiple Action Research cycles. Action Research (although limited by its practical relevance rather than statistical generalization) in nature, means selected industrial cities were sufficient to afford

adequate depth, diversity, and stakeholder engagement to enable detailed iterative learning cycles.

The research followed the standard Action Research cycle as outlined in the context for diagnosis, planning, action/intervention, observation, and reflection (Reason & Bradbury, 2018; Kemmis et al., 2014).

This cyclical structure helped to find the architectural barriers, devise AI-enabled intervention designs, monitor outcomes, and refresh approaches against the feedback of stakeholders.

This structure corresponds with the action research principles behind EIU, which are about real-world problems, precise interventions, and reflection on learning with the right mindset.

Enterprise Architecture strategy governance, capability alignment, digital transformation, and technology direction are centrally driven by Enterprise Architects, IT Directors, Business Capability Owners, Operations Managers and Digital Transformation Leads at the headquarters.

While this centralized governance structure alongside distributed city-level environments offers a broad-based, but practically accurate, overview of the ecosystem of enterprise architecture.

11 industrial cities included to achieve balanced architectural coverage of the architecture, which is in accordance with the principles of Action Research, whereby sampling adequacy is defined as relevance and stakeholder participation.

2.1 Diagnosis Phase

This included baseline assessments during diagnosis, as per the stage to involve:

- Semi structured interviews.
- System audits.
- Review of existing EA documentation.
- Analysis of legacy system inventories.
- Evaluation of technical debt indicators.
- Mapping of undocumented integration points.

The diagnosis found the following across all organizations:

- The baseline EA documentation accuracy (60–65%) was determined by manual audits and cross-checking against actual system inventories and integration points based on established EA quality assessment techniques (Lankhorst, 2017; Ross et al., 2006; Kruchten et al., 2012).
- 20–30 working days per capability were needed for architectural mapping.
- Technical debt was high and not clearly measured.
- Integration points were not consistently documented.
- Limited visibility to architectural risks for business stakeholders.

It validated that legacy EA practices were inadequate for Industry 4.0 modernization.

2.2 Planning Phase

During the planning stage, AI based EA modernization intervention was developed. An interactive intervention was produced by stakeholders to develop the intervention to ensure practical relevance of the intervention and the organization endorsement of the intervention. Planning consisted of:

1. Choosing AI tools for automated architectural discovery.
2. Building machine learning models for dependency analysis.
3. Designing predictive models for technical debt.
4. Creating dynamic visualization dashboards.
5. Setting up governance standards for data quality.
6. Training EA teams on AI literacy and interpretation.

In the initial phase of the process collaboration, practicality and alignment to organizational priorities was noted (Herr & Anderson, 2015): the action research principles used should apply.

3. Action / Intervention

At the diagnosis stage, the intervention included four principal AI-enabling actions tailored to a unique EA challenge. Using AI for Automated Architectural Discovery

Conventional architectural discovery is based on hand-interviews, static diagrams and old models & documentation.

To address this, the intervention deployed AI tools that can:

- Natural Language Processing (NLP) for system documentation reading.
- Automating the scanning of APIs, configuration files, and code repositories.
- Analysis of network traffic to find out when systems interact in real time.
- Automatic building of architectural baselines.

The AI ingestion of thousands of pages of documentation was followed by automatic dynamic maps for architecture. This shortened the time to map from 20-30 days to 3-4 days, achieving a loss of more than 70% in time, aligned with the industry results (Accenture, 2023).

This approach enables us to model the dependence of models by using Graph Machine Learning. Industrial cities are known for complex system dependencies that are difficult to visualize via manual extraction. Graph Machine Learning (Graph ML) was used to analyze the intervention:

- Application to application dependencies.
- Database relationships.
- Middleware interactions.
- Legacy system touchpoints.
- Hidden integration chains.

Graph ML uncovered several critical “single points of failure” that hadn’t been captured before. A manufacturing organization, for instance, identified that its core production line scheduling system relied on an undocumented legacy database, an incredible operational risk.

This is consistent with international research which shows that AI can reveal dependencies that human architects commonly don’t (McKinsey & Company, 2023).

Forecasting Technical Debt Modelling in an Industry. Technical debt stands as a major obstacle to modernization in industrial cities. The intervention used machine learning regression models to analyze:

- Incident logs.
- Outage histories.
- Patch frequencies.
- Maintenance costs.
- Legacy framework usage.
- Security vulnerabilities.

The AI produced a Technical Debt Risk Score for each application. This score estimated the odds of failure over the next 6 to 12 months.

To put these insights into practice, organizations set the priorities of modernization investments.

The predictive capability changed EA from a reactive documentation function into an approach to mitigate risk proactively (Kruchten et al., 2012).

Dynamic Visualization Dashboards. Applying AI driven visualization dashboards to keep business stakeholders aware of accessibility was one way the intervention was done.

These dashboards:

- Showed contemporary architectural drawings.
- Highlighted risk levels.
- Permitted Natural Language Queries
- Assisted with impact analysis for modernization decision making.
- Facilitated cross functional cooperation.

Questions business leaders might ask include:

- **What systems will take a hit if we overhaul the logistics management platform?**

The AI produces a color-coded impact map instantly.

This enhanced communication between business and IT stakeholders, in line with EA literature which has highlighted the need for shared visibility (Ross et al., 2006).

4. Findings

For all involved organizations, the Action Research intervention yielded significant and measurable gains in Saudi Arabia's traditional industrial cities.

The results show that AI-enabled Enterprise Architecture (EA) improves architectural visibility, minimizes technical debt burden, speeds up modernization, and fosters cross functional collaboration. As a result, these outcomes confirm previous studies in the international community that found that AI can enhance EA accuracy, speed, and value to the overall value proposition (Accenture, 2023; McKinsey & Company, 2023). The findings are classified into four key outcome categories:

1. Architectural mapping and discovery acceleration
2. Increased accuracy of data and completeness of architectural components
3. Decrease of Technical Debt and Operational Risk
4. The IT to Business Alignment and Decision-Making Strengthening

4.1 Rapid Acceleration of Architectural Mapping & Discovery

4.1.1 Inefficient Time to Mapping

Prior to the intervention, architectural mapping took 20–30 working days per business capability. This was due to:

- Manual interviews
- Siloed documentation
- Outdated diagrams
- Incomplete system inventories

After deploying AI-enabled discovery tools, mapping time dropped to 3–4 days, representing a 70–80 percent cut. That result, based on the findings published by Accenture (2023), matches industry studies that conclude architectural discovery can be automated by AI and manual effort reduced by more than 60%.

4.1.2 Real-time Architectural Visibility

AI tools continuously scanned:

- APIs
- Configuration files
- Network traffic
- Code repositories

That created a dynamic architectural baseline which updated automatically.

Organizations claimed that having this visibility in real time was the first time they had had “living architecture” as opposed to static diagrams. This change of architecture configuration from static to dynamic forms is in accordance with the global EA modernization movements (Ross et al., 2006).

4.2 Reduction in Non-Compliance Data and Architectural Completeness

4.2.1 Higher Accuracy for Documentation

Baseline documentation accuracy was between 60–65% on average, with the following assumptions:

- Missing integration points
- Outdated system inventories
- Inconsistent naming conventions
- Shadow IT usage

Accuracy, 92–94% after intervention, was confirmed through manual audits, verified and cross checked to the AI mapped. This increase agrees with the results of Graph Machine Learning study which demonstrated that AI could discover latent dependencies invisible to the human architect (Lu, 2017).

4.2.2 Shadow System Identification

AI discovered:

- Undocumented legacy databases
- Unauthorized applications
- Hidden point-to-point integrations

- Deprecated middleware components

In one manufacturing organization, AI found 17 undocumented integration points in 2025 that posed a significant operational risk. This result is consistent with international work finding that undocumented procedures are a significant portion of technical debt (Kruchten et al., 2012).

4.3 Debt-to-operational ratio will decline

4.3.1 The Predictive Technical Debt Model

Predictive models were analyzed, AI enabled:

- Incident logs
- Outage histories
- Patch frequencies
- Legacy framework usage
- Security vulnerabilities

The models resulted in a Technical Debt Risk Score for each application, reflecting the probability of failure occurring within 6-12 months.

High-risk legacy components were identified in three participating entities. The three were updated proactively, avoiding predicted failures. This result illustrates the usefulness of predictive analytics in EA, on par with other industry studies (World Economic Forum, 2020).

4.3.2 Incident frequency was reduced

Organizations reported:

- Fewer unplanned outages
- Quicker root cause analysis
- Enhanced maintenance prioritization

A logistics company in Jeddah Industrial City decreased high severity incidents by 40% within three months.

4.3.3 Better Modernization Roadmaps

AI insights empowered organizations to apply the following:

- Risk-based modernization priorities
- Optimize sequences for upgrades
- More strategically allocated budgets

This change has transformed modernization planning from intuition oriented to data oriented.

4.4 Enhancing Business-IT Alignment and Decision Making

4.4.1 Increase in Cross Functional Collaboration

AI driven dashboards provided:

- Real time architectural maps
- Color coded risk indicators
- Natural language queries
- Visualizations of impact analysis

Decision makers might consider the following questions as part of reflective inquiry and organizational learning (Reason & Bradbury, 2018):

- What systems will be impacted if we upgrade the production scheduling platform?

An impact map was instantly created by AI This strengthened the dialogue on business & IT team communications and aligns with EA research highlighting shared visibility (Ross et al., 2006).

4.4.2 Improved Strategic Decision Making

Effective strategic decision-making was invariably manifested in all participating organizations. A percentage-based descriptor is used to describe the distribution of the responses and enables a clearer distinction between areas of improvement, while preserving methodological rigor.

- 90% of attendees say getting AI-enabled architectural visibility led to shorter decision-making cycles with evaluation and approval times.

- 85% of those surveyed reported that modernization planning was now more confident, indicating that data-driven insights helped prioritize and sequence modernization initiatives.
- Overall response improved by around 80% when it comes to alignment with Industry 4.0 programs, indicating that the respondents were more inclined to embrace advanced industrial technologies and digital manufacturing capabilities.
- 75% of respondents reported improved maturity in governance, indicating that AI-supported architectural clarity resulted in more structured, consistent, and transparent governance practices.

A CIO from one industrial city has shared a qualitative insight too, saying that “AI has turned architecture into a strategic asset rather than a form of document collection”.

4.4.3 Improved readiness for Industry 4.0

AI empowered EA to be more prepared on:

- IoT integration
- Predictive maintenance
- Cyber physical systems
- Smart manufacturing
- Digital twins

Organizations appeared to be more able to adopt Industry 4.0 technology, as indicated in international studies (Kagermann et al., 2013).

4.5 Quantitative Summary of results

Table 4.5.1 provides a summary of the quantitative outcomes of the intervention.

Baseline values, post-intervention outcomes, and measured improvements across all participating industrial city organizations are shown in the table.

Outcome Type	Baseline	Post-Intervention	Improvement
Architectural Mapping Time	20-30 days	3-4 days	70-80% faster
Documentation Accuracy	60-65%	92-94%	+30% improved
High-Severity Incidents	Baseline varies	-40%	Significant reduction
Shadow Systems Identified	Unknown	10-20 per org	Major visibility gain
Business-IT Alignment	Low	High	Qualitative improvement

Table 4.5.1

The quantitative results from Table 4.5.1 can be helpful in interpreting some observations as follows:

- Architectural mapping time improved the most and could be reduced by up to 80%, suggesting that AI-enabled discovery significantly accelerated architectural visibility.
- Documentation accuracy increased by approximately 30 percentage points, demonstrating that AI-supported mapping produced more complete and reliable architectural baselines.
- A 40% reduction in high-severity incidents is indicative of predictive analytics in identifying and mitigating operational risks.
- Shadow system identification exposed previously unknown components, with 10-20 undocumented systems detected per organization, which highlighted the extent to which hidden technical debt lies.
- Business-IT alignment, qualitatively, improved among organizations with greater transparency and shared architectural visibility, resulting in better quality in decision-making.

The quantitative results collectively show measurable benefits of AI-enabled enterprise architecture across all involved industrial city organizations, in operational, architectural, and strategic terms.

4.6 Overall interpretation of results

The findings show that AI enabled EA is a strategic instrument for industrial modernization among traditional Saudi industrial cities. The intervention produced:

- Faster architectural discovery
- More accurate documentation
- Lower technical debt
- Reduced operational risk
- Better business–IT relationship
- Enhanced readiness for Industry 4.0

These results strengthen the theory that using AI can change EA from a static form of documentation to a dynamic, intelligence driven capability.

5. Reflection on the Action Research Process

An Action Research intervention across Saudi Arabia's legacy industrial cities had obtained the following deep insights into the nature of EA, the role of AI and the organizational context in which it is challenging to digital transform.

The steps of such iterative (Plan → Act → Observe → Reflect) loops allowed participants to learn, adapt and update, paralleling the principles found in Action Research (Reason & Bradbury, 2018; Kemmis et al., 2014).

5.1 Reflection on EA Practice Before AI

EA teams across the participating organizations functioned in environments prior to the intervention characterized by:

- Fragmented documentation
- Siloed system knowledge
- High technical debt
- Limited architectural visibility
- Reactive decision making

These conditions fostered an environment where EA became the perception of EA just as a documentation item and not a strategic capability. Numerous architects felt frustrated because, upon completion of work, their work was obsolete, they said.

This line of thought resonates with global research findings of EA literature documenting that traditional manual EA approaches are ill-equipped to keep pace with today's digital environments (Lankhorst, 2017; Ross et al., 2006).

5.2 Reflection on the Impact of AI Enabled EA

AI enabled EA teams to understand how their role and value changed significantly.

Several reflections emerged:

5.2.1 EA Became a Capability in Real Time

AI turned EA from a static retrospective role of EA into an intelligence capability in ‘real time’. Architects reflected that they could finally:

- See accurate system dependencies
- Identify hidden risks
- Instantly understand architectural impact
- Support confident business decisions

This adjustment reflects worldwide findings that show how AI boosts EA agility and responsiveness (Accenture, 2023).

5.2.2 EA Teams Transitioned from “Documenters” to “Advisors”

By using AI to do discovery and dependency mapping, architects could now focus on:

- Strategic planning
- Risk analysis
- Modernization roadmaps
- Business alignment

This observation is echoed in studies that reveal AI transforms architects into strategic advisors (McKinsey & Company, 2023).

5.2.3 Business Stakeholders Became More Engaged

AI powered dashboards simplified architecture for non-specialists of management. As business stakeholders described:

- Architecture became “visible”
- Risks became “real”
- Decisions were “data driven”
- Collaboration became “easier”

This increasing alignment aligns with those provided in EA literature which encourages shared visibility (Ross et al., 2006).

5.3 Reflection on Organizational Culture

The intervention showed that technology alone can't suffice. Organizational culture is a critical factor in EA modernization.

5.3.1 Data Governance Is Fundamental

AI exposed inconsistencies in:

- Naming conventions
- Documentation quality
- Integration records
- System inventories

Architects agreed that if governance is weak, AI amplifies data problems. This aligns with the “garbage in, garbage out” principle widely cited in AI research (Westerman et al., 2014).

5.3.2 Cross Functional Collaboration Must Be Strengthened

Upgrading EA is not an independent, siloed endeavor. It requires collaboration between:

- IT
- Operations
- Business units
- Cybersecurity
- Finance

Many organizations simply lacked structured collaboration mechanisms, with reflection sessions confirming this. AI has contributed to bridge this gap, but governance arrangements need to be reinforced to maintain this level.

5.3.3 Capability Building Is Critical

EA teams indicated that they require new skills:

- AI literacy
- Data interpretation
- Visualization analysis
- Predictive modeling
- Business communication

This is consistent with global evidence that digital transformation needs new skillsets (Schein, 2010).

5.4 Implications for Practice

The reflections identified in the Action Research cycles outline various implications for practice that are directly pertinent to industrial organizations that would like to modernize enterprise architecture with AI-enabled solutions.

These implications go beyond operational enhancements and point to structural, cultural, and strategic factors an enterprise must consider for EA modernization to thrive.

5.4.1 AI Enabled EA as standard practice

The intervention demonstrated that AI enables significantly better architectural accuracy, velocity, and risk visibility. Taken together, these gains suggest that AI-enabled EA should be the default operating mode, considering that manual methods are unable to sustain modernization in complex industrial environments.

5.4.2 Establish Enterprise Architecture Governance boards

Governance committees provide oversight to regularly revisit architectural risks, technical debt, and modernization priorities to maintain alignment of EA with strategic end goals rather than individual activities, with the purpose of moving EA to an area where architectural risks do not hinder EA from deriving strategic outcomes but continue the cycle.

5.4.3 Invest in Data Governance and Quality

AI-enhanced EA requires reliable and consistent data for EA to be effective; it relies on the use of coherent data. Deepening the strength of naming conventions, systems inventories and documentation around system integration, which can ensure quality of the data and systems documentation to ensure that the output of AI becomes accurate and actionable and not the result of poor-quality data in the form of architectural insights of poor quality will be at odds for EA insight.

5.4.4 Build EA Capability Through Training and Upskilling

EA teams need to learn how to work more appropriately with AI-based tools. Analytical, visual and communicative proficiency in analytics, visualization and communication allow architects to understand AI insights and contribute strategically, unlike manual documentation.

5.5 Integrate EA into Strategic Decision Making

AI-enabled EA delivers real-time architectural intelligence for strategic planning. The implementation of EA in budgeting, modernization roadmaps and risk management ensures the effectiveness of decision-making and that it is evidence-based and supportive of the long-term transformation objectives.

5.6 Use AI to Prioritize Modernization Investments

AI-generated risk scores provided an objective approach to modernization sequencing. By ranking investment by technical debt and system risk, modernization efforts will now directly address the areas most affected operationally and strategically.

5.7 Adopt Dynamic Visualization Dashboards for Business Alignment

For non-technical leaders, visualization dashboards help architecture make sense. Demonstrating them in executive and operational forums reinforces business-to-IT alignment and promotes collaborative decision-making with architectural transparency.

5.8 Scale the AI Enabled EA Model Across All Industrial Cities

The intervention was successful across various organizations so this model can be scaled nationally. Standardization of tools and practices across industrial cities helps ensure reliable modernization and supports the objectives of Vision 2030's digital transformation strategy objectives.

Conclusion

This Action Research study aimed to investigate the role of AI in modernizing EA practices in Saudi Arabia's traditional industrial cities and facilitating the adoption of Industry 4.0 readiness.

Based on (Plan → Act → Observe → Reflect) cycles, the study made clear that AI enabled EA was more than a technological enhancement, but a strategic capability that transformed how all organizations should understand their digital ecosystems, their management, and their modernization.

In that 11-organization sample, the research suggested that simple EA practices, such as manual documentation, siloed knowledge, and static architectural diagrams, fail to keep up with recent industrial environment complexities and speed. And this limitation added an architectural bottleneck slowing modernization and technical debt, impeding decision-making.

Diagnosis phase confirmed the average accuracy of architectural documentation was just 60–65%, mapping processes took 20–30 working days, and technical debt was not well quantified.

These findings are consistent with international studies that demonstrate traditional EA frameworks fail to keep pace with changing digital ecosystems (Lankhorst, 2017; Ross et al., 2006).

The intervention that AI emulated was transformative. Automated architectural discovery decreased more than 70% from what it existed before, Graph Machine Learning uncovered unexpected dependencies and predictive technical debt models provided forward looking information about risks.

Documentation accuracy soared to 92–94%, and several organizations took initiative to upgrade high risk legacy components flagged by AI.

These findings add further confirmation of findings by the industry that AI can accelerate architectural analysis and decision-making immensely (Accenture, 2023; McKinsey & Company, 2023).

More than merely improving the technical aspects of that intervention was the significant organizational change that was achieved.

EA teams transitioned from “documenters” to strategic advisors, business entities saw architectural risks in real time, business stakeholders had access to insights at the same time as stakeholders in the market, and cross-functional collaboration increased significantly.

AI powered dashboards made architecture accessible to non-technical leadership and made modernization decisions more informed and confident.

The resulting improved alignment between business and IT attests to the strategic significance of EA highlighted in international literature (Ross et al., 2006). Several essential lessons were pointed out by the reflection phase.

- First, AI data governance must be strong; without neat metadata and a regular documentation process, AI insights cannot be trusted.
- Second, EA practitioners should acquire new skills related to analytics, visualization, or AI literacy.
- Third, AI adds rather than displaces human judgement. AI can recognize and identify patterns and assess risks, but architects need to place such observations in contextual frameworks of organization, politics, and strategy.
- Finally, AI empowered EA facilitates the development of adaptive operating practices that adapt to technological change with maximum agility and robustness. It is concluded in the article that AI empowered EA is a strategic driver for industrial modernization in Saudi Arabia.

This model is highly replicable for industrial cities aspiring to strengthen architectural governance, reduce technical debt, and accelerate digital transformation.

The results align well with the national priorities on Vision 2030, including digital capability building, industrial diversification, and smarter infrastructure.

AI-based EA presents a route back toward sustainable modernization, operational resilience, and preparedness for Industry 4.0 technologies as industrial communities evolve. In an increasingly digital-industrial landscape, organizations that adopt this model will be best able to navigate complexity, mitigate risk, and create value over the long-term.

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